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Researching the causes and consequences of unemployment

The Heterogeneous Labor Market Impacts of the Covid-19 Pandemic

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ABSTRACT

We study the distributional consequences of the Covid-19 pandemic's impacts on employment. Using CPS data on stocks and flows, we show that the pandemic has exacerbated pre-existing inequalities. Although employment losses have been widespread, they have been substantially larger in lower-paying occupations and industries. Individuals from disadvantaged groups, such as Hispanics, younger workers, those with lower levels of education, and women, have suffered both larger increases in job losses and larger decreases in hiring rates. Occupational and industry affiliation can explain only part of the increased job losses among these groups.

JEL Classification Codes: E24, J21, J31, J62, J63

Key Words: Covid-19, CPS, job losses, occupations, industries, distributional impacts

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1 Introduction

The Covid-19 pandemic led to a 10.3 percentage point increase in the unemployment rate in April 2020 (BLS, 2020). A fifth of individuals who were employed in February 2020 were no longer employed as of mid-April.[1] Although no sector of the economy was left unscathed, employment losses were especially severe in industries such as food services, recreation, and accommodation (BLS, 2020). In this paper we analyze the heterogeneity of the pandemic-induced employment losses across occupations, industries, and demographic groups, and the distributional consequences of these changes.

Using data through April 2020 from the Current Population Survey (CPS) — the primary source of labor force statistics for the United States — we document three key facts. First, we show that the pandemic-induced reductions in employment, and the associated increases in employment exit rates and decreases in hiring rates, were disproportionately concentrated in low-wage jobs. Service sector employment suffered the worst outcomes, but even within service sector industries, job losses were greater for lower-wage occupations. Second, we show that job losses were disproportionately concentrated among younger workers, those with less education, racial and ethnic minorities, and women. Third, we show that, with the exception of women, the disproportionate job losses for workers from disadvantaged groups cannot be fully explained by their pre-pandemic industry and occupation affiliation.

We match individuals across months in the CPS in order to identify individuals who were employed before the pandemic (in February 2020) and follow them through March and April. We find that 40% of individuals who exited employment between February and April are now classified as out-of-the-labor-force. Further, we show the massive decrease in employment in April 2020 was driven by individuals exiting employment, with over 90% of the decrease in employment due to exits and the balance attributable to reduced hiring. This is in contrast to evidence from previous recessions that firm hiring is the dominant factor driving employment declines (c.f. Elsby et al., 2009; Fujita & Ramey, 2009; Shimer, 2012).

We rank occupations and industries according to their average wages before the onset of the pandemic, following the literature on labor market polarization (e.g. Acemoglu & Autor, 2011; Autor et al., 2006; Goos & Manning, 2007).[2] We then use

[1]See Figure 1.

[2]We use the average wage in January and February 2020; the ranking is nearly identical if we use the average wage in 2019.

a regression-based approach in order to isolate the impact of the pandemic on employment at different points of the distribution from occupation- or industry-specific seasonal patterns and longer-term trends.[3]

Our results indicate that the decline in employment and the associated increase in the employment exit rate observed during the pandemic were disproportionately concentrated in lower-paying occupations and industries. Some of the highest-paid occupations, such as Architecture and Engineering, and Computer and Mathematical Occupations, in fact saw negligible declines in employment, whereas nearly all occupations in the bottom quartile of the occupational wage distribution experienced strong employment declines. Similar patterns are observed across industries. This indicates that the pandemic is exacerbating pre-existing inequalities, with the impacts being most strongly felt among individuals in lower-paying jobs.[4] Notably, we also find that the disproportionate negative impacts on lower-paying occupations are also observed *within* industries.

Turning to the heterogeneous impact of the pandemic across demographic groups, we find that young, less educated, non-white workers, and women experienced the largest employment losses. These workers are disproportionately employed in low-wage and service sector jobs, and hence their increased rates of job loss can be partially explained by their pre-displacement industry and occupation affiliations. Importantly, however, we find that, for most disadvantaged groups, at least 25% of the increase in job loss occurs *within* detailed occupations and industries, implying that workers from these disadvantaged groups saw more severe employment losses even when compared with other workers in similar jobs. This is further confirmed by the fact that most occupations experienced a decline in the within-occupation share of young, less-educated, and non-white workers between February and April. A similar pattern is also observed within industries. Women are the exception, with job losses fully explained by sex segregation into jobs that experienced larger losses.

The literature on the labor market impacts of Covid-19 is growing rapidly. A burgeoning literature uses O*NET occupational characteristics to evaluate which jobs can be performed remotely and which jobs are likely to be at risk due to social distancing

[3]Given the magnitude of the shock induced by the pandemic, our qualitative results are not sensitive to the approach taken to control for seasonality and/or longer term trends.

[4]Though we focus only on employment outcomes, an additional factor exacerbating these already stark inequalities is the possibility that those who remain employed in these lower-paying occupations are increasingly exposed to the virus due to the limited possibilities of remote working offered by these occupations (see e.g. Ruiz-Euler et al., 2020).

requirements. Dingel & Neiman (2020) classify occupations according to whether or not they can be performed remotely, which Montenovo et al. (2020), Mongey et al. (2020), and Béland et al. (2020) build upon, showing better labor market outcomes for workers in occupations that were more likely to be able to work from home or were less likely to have to work in close proximity to others. Kahn et al. (2020), however, show that the rise in unemployment claims and the fall in vacancy postings through April are not well explained by whether the occupation can work-from-home, indicating the economic slowdown is broad-based.

Our work complements these contributions by highlighting the distributional effects across occupations and industries and the disproportionate impacts on workers in lower-paid jobs. Our evidence is in line with the findings of Hoynes et al. (2012) regarding the disproportionate impacts of previous recessions on individuals who were already economically disadvantaged. Related evidence on the disproportionate impact of the Covid-19 shock on lower paid workers is presented by Cajner et al. (2020) using data from ADP, a large U.S. payroll processing company.[5] Using CPS data, and consistent with our findings, Montenovo et al. (2020) find larger decreases in employment for Hispanics, workers aged 20 to 24, and those with high school degrees and some college. By ranking occupations and industries in terms of their mean wages, and thus structuring our analysis along distributional lines, our results complement their findings, which focus on occupational task dimensions. Moreover, by exploiting labor market flows, we are able to consider the role of pre-displacement occupational and industry affiliation in accounting for the differentials observed across demographic groups not only for unemployed workers but also for those who transition to being classified as being out of the labor force.[6]

2 Data and Aggregate Patterns

Our analysis is based on monthly data from the Current Population Survey (CPS). The CPS is sponsored jointly by the U.S. Census Bureau and the U.S. Bureau of Labor

[5]See also Adams-Prassl et al. (2020), who conduct a survey in the UK, and find that young workers and lower-income individuals are disproportionately likely to have lost their job or suffered hours losses.

[6]We find that 40% of individuals who exited employment between February and April are now classified as out-of-the-labor-force. Given that the CPS does not record prior occupation or industry information for individuals who are out of the labor force (outside of those in the outgoing rotation groups), an analysis that aims to understand the role of prior occupation and industry based solely on cross-sectional data would miss an important fraction of the workers suffering Covid-induced job losses.

Statistics (BLS). We rely on the microdata made publicly available by IPUMS (Flood et al., 2018). To construct employment flows, we follow Madrian & Lefgren (1999), matching monthly files using administrative IDs and confirming matches based on sex, race, and age. We restrict the sample to non-institutionalized civilians aged 16 and older. Most specifications use data from January 2015 through April 2020.

The CPS records respondents' labor market status during a particular reference week, which is always the week that spans the 12th of the month. For March 2020 the reference week was March 8–14 and for April 2020 it was April 12–18. The majority of the major lock-down orders and other strict social distancing measures had not yet been implemented by the time of the March survey.[7] Hence, the March 2020 CPS data only captures the very early effects of the Covid-19 pandemic. For most of the analysis, we focus on the patterns observed in April 2020, using earlier data to make adjustments for seasonal patterns and time trends as discussed in further detail below. All patterns shown are based on weighted outcomes using CPS composite weights.[8]

Figure 1 displays overall aggregate patterns over time. Panel A shows the evolution of the employment rate since January 1976. The solid blue line is the standard official employment rate, using all individuals who are classified as employed in a given month. The dashed red line displays an adjusted employment rate which excludes certain individuals who are likely to have been mis-classified as employed during the pandemic. Specifically, in April 2020, there was a large increase in the group of individuals who report that they were employed but absent from work for reasons other than the ones enumerated by the CPS (such as vacation or illness). While this group is typically less than 0.5% of the population, it grew to almost 5% in April 2020. The BLS has argued that these individuals who are absent for "other" reasons should likely be classified as

[7]Data from the Department of Labor shows that initial unemployment insurance claims totaled 250,892 in the week ending March 14 – a substantial increase relative to the previous week (25.2 percent), but nowhere near the unprecedented levels that were observed in subsequent weeks (see `https://www.dol.gov/ui/data.pdf`).

[8]Between 95,000 and 100,000 working-aged individuals are sampled by the CPS each month. Response rates fell during the pandemic, to 85,000 in March and 82,000 in April. For our flow analysis, this implies that (non-scheduled) attrition from the sample increases from around 8% between 2015 and 2019 to around 13% during the pandemic. The BLS, however, has stated that "although the collection rates were adversely affected by pandemic-related issues, BLS was still able to obtain estimates that met our standards for accuracy and reliability" (https://www.bls.gov/cps/employment-situation-covid19-faq-april-2020.pdf). For the flow analysis, we weight using the most recent month's weights in order to account for attrition over recent months. Our results also confirm that the patterns observed in the flow data are very consistent with the observed changes in stocks along the different dimensions that we consider.

temporary layoffs.[9] However, nearly one-quarter of individuals who were absent for "other" reasons in April 2020 report being paid by their employer for their time off. We therefore compute an adjusted employment rate (shown by the red dashed line) that excludes individuals who are classified as employed but (i) were absent from work during the reference week, (ii) report being absent for "other" reasons, and (iii) report that they were not paid by their employer for their time off.[10] Workers satisfying these three criteria are instead classified as unemployed.

Regardless of whether the standard or the adjusted employment rate is considered, the decline observed in April 2020 is very dramatic by historical standards. The official employment rate falls from 60.8% in February to 51.3% in April 2020. The adjusted employment rate, which historically differs from the official employment rate only marginally, falls further, from 60.7% in February to 48.9% in April. We use these adjusted measures of employment and non-employment for the remainder of our analysis.

Panels B and C of Figure 1 illustrate the associated labor market flows between employment and non-employment since January 1994. Each flow is expressed as a share of employment in the previous month. Panel B shows that outflows from employment to unemployment and not-in-the-labor-force (NILF) both increased dramatically in April 2020. From 2015 through 2019, the average monthly exit rate to unemployment was 1.4%. This increased to 2.6% in March 2020 and 14.8% in April 2020. Exits to NILF averaged 3.1% from 2015 through 2019, but increased to 3.4% in March 2020 and 6.3% in April 2020. Thus, 21% of individuals employed in February 2020 were no longer employed by April.

Panel C of Figure 1 displays the hire rates from from unemployment and NILF as shares of the previous month's employment. Here we see that the inflow rate has also changed, but less dramatically. Hire rates from unemployment averaged 1.0% from 2015 to 2019, but fell to 0.78% in March 2020 and 0.76% in April 2020. Hires from NILF averaged 2.1% from 2015 through 2019, but fell to 1.8% in March 2020 and 1.2% in April. However, compared to the four-fold increase in exit rates, hiring remains comparatively robust by April 2020.

These results indicate that over 90% of the dramatic rise in non-employment is due to exits from employment, rather than decreased hiring. This contrasts with the pattern

[9] https://www.bls.gov/cps/employment-situation-covid19-faq-april-2020.pdf

[10] Given the magnitude of the shock, this adjustment is not crucial for any of the qualitative patterns that we document in the paper.

typically observed during recessions, where a collapse in hiring is usually the dominant driver of increased unemployment rates (c.f. Elsby et al., 2009; Fujita & Ramey, 2009; Shimer, 2012).

Isolating the impact of the pandemic from seasonal patterns and time trends

Our paper explores heterogeneities in the employment effects of the pandemic across occupations, industries, and demographic groups. In order to isolate the pandemic-related changes from patterns related to seasonality or longer-term time trends (which may be particularly important for certain occupations, industries, or demographic groups), we estimate a series of regressions using data from January 2015 to April 2020. The regressions are estimated using collapsed data at the group level for each month (where groups may be either occupations, industries or demographic categories), and are run separately for each group. The regression takes the following form:

$$Y_{gt} = \gamma_g D_{m(t)} + \alpha_g D_{y(t)} + \theta_g D_{2020M3} + \delta_g D_{2020M4} + \epsilon_{gt} \tag{1}$$

Y_{gt} is the outcome variable of interest for group g in period t. For the stock analysis, this is the employment rate of group g in a given month. For hires and exits, we use matched data over two-month windows (e.g. February–April), and calculate the rates of hiring and exiting as shares of employment in the first month of the window.[11] $D_{m(t)}$ is a vector of calendar month dummies. The coefficient γ_g captures any seasonal variation in outcomes that are specific to the group being considered. $D_{y(t)}$ is a vector of year dummies, so that α_g accounts for year-by-year variation in the outcome of interest for the specific group. D_{2020M3} and D_{2020M4} are dummies for March and April 2020, respectively.[12] We include the March 2020 dummy given that some important deviations in outcomes are already observed in that month. However, our key coefficient of interest is δ_g, which captures group-specific deviations in the outcome of interest in April 2020, once seasonal effects and longer-run time trends have been accounted for. While our analysis focuses on the estimated pandemic-related effects $\widehat{\delta}_g$, results are qualitatively similar if focusing on raw changes over time, given that the resulting adjustments for seasonality and time trends are relatively small compared to the magnitude of the Covid

[11]We prefer the use of two-month windows given that the effects of the pandemic start to be noticeable in the data in March 2020. The two-month window from February to April 2020 therefore captures the full effect of the pandemic.

[12]In the matched data, April 2020, for example, represents an indicator variable for individuals who are matched from February 2020 to April 2020.

shock.

3 Distributional Impacts of the Covid-19 Pandemic

As is well known, the Covid-19 crisis has led many sectors of the economy to be shut down, while also requiring production to be severely altered in other sectors. Under shelter-in-place orders only essential businesses are allowed to operate, while all other businesses must suspend operations or have their employees work remotely. Even in states that do not have strict shelter-in-place laws, consumer spending patterns have shown a dramatic slowdown in business for restaurants, gyms, and hair salons.[13] Thus, we expect significantly heterogeneous impacts across different types of jobs, leading to differential impacts across workers, with potentially important distributional implications.

3.1 Heterogeneous Impacts across Occupations and Industries

Following a similar approach to the literature on job polarization (e.g. Acemoglu & Autor, 2011), we analyze the distributional impacts of the pandemic by ranking occupations and industries based on their mean hourly wages in the pre-crisis period of January and February 2020.[14] For occupations, we focus on 22 2-digit SOC occupations, which are detailed in Table 1 (ranked from lowest- to highest-paying).[15] The lowest-paying occupations include Food Preparation and Serving, Personal Care, and Cleaning and Maintenance Occupations, while the highest-paying occupations include Management, Legal, and Computer and Mathematical Occupations. For industries, we focus on 13 major industry categories, which are listed in Table 2 (also from lowest- to highest-paying). The lowest-paying industries include Leisure, Hospitality and Trade, while the highest-paying include Professional and Business Services, Financial Activities, and Mining.

[13] See for instance https://slate.com/business/2020/05/south-reopening-restaurants-coronavirus-opentable.html

[14] The ranking is nearly identical if we use average wages for 2019. Hourly wages are taken directly from the data if available, or computed as weekly earnings divided by usual (or actual) hours worked per week. As in Lemieux (2006), top-coded earnings are adjusted by a factor of 1.4. We convert nominal values to 2009 dollars based on the monthly Consumer Price Index (CPI, All Urban Consumers) from the BLS.

[15] Some results at a finer occupational level are presented in the Appendix. While occupational codes used in the CPS changed in January 2020 (from 2010 to 2018 Census code categories), the changes are relatively minor and do not affect the comparability over time at the 2-digit SOC level.

Figure 2 explores how the employment losses observed in aggregate as of April 2020 are distributed across occupations. The figure plots the estimated coefficient $\widehat{\delta}_g$ from Equation (1) for each 2-digit occupation (indicating the change in the dependent variable in April 2020 after controlling for seasonality and year fixed effects), along with a 95% confidence interval. Occupations are ranked from lowest-paying on the left to highest-paying on the right, as listed in Table 1. Panel A plots the changes in employment rates (employment in each occupation as a share of the total population). A clear pattern emerges: the impact of the pandemic is quite heterogeneous across occupations, with lower-paying occupations experiencing significantly larger contractions in employment. In particular, the 12 lowest-paying occupations experience statistically significant and quantitatively large declines in employment, with the only exception being Farming, Fishing and Forestry occupations (wage rank 3).[16] Meanwhile, neither Architecture and Engineering Occupations (the third-highest paying) nor Computer and Mathematical Occupations (the highest-paying in the sample) experience statistically significant employment declines; in fact, Computer and Mathematical Occupations are the only ones to experience an increase in employment during the pandemic, although this increase is not statistically significant.

Appendix Figure A.1 plots the raw changes in employment rates between February and April 2020 using information at the more granular 4-digit occupation level. Occupations are assigned to (employment-weighted) percentiles based on their mean wage in the pre-pandemic period of January and February 2020. The figure plots changes in employment per capita for occupations at each percentile of the distribution. This confirms our finding that the impacts of the pandemic were much stronger for lower-paying occupations. The occupations with the largest employment declines, which account for more than a quarter of a percentage point decline in the aggregate employment rate each, include waiters (1st percentile), cashiers (4th), cooks (7th), maids (9th), laborers (18th) and retail salespersons (20th).[17]

In Panels B and C of Figure 2 we examine the hire rate from non-employment and the exit rate to non-employment for each occupation. These rates are calculated as a share of employment in the first month of the 2-month span, so the rate in April 2020

[16] The other two low-paying occupations with relatively small employment declines are Healthcare Support Occupations (ranked 5th) and Protective Service Occupations (ranked 10th).

[17] There are also some notable exceptions. Occupations with below-median wages that experience increases in employment per capita between February and April 2020 include religious workers (12th percentile), couriers and messengers (26th), eligibility interviewers for government programs (31st), farmers (37th), public safety telecommunicators (40th), and emergency medical technicians (47th).

is expressed as a share of employment in February 2020. This puts both inflows and outflows on the same denominator, which makes it easier to compare relative magnitudes.[18]

Consistent with what we saw in Figure 1, the magnitude of the increase in exit rates shown in Panel C dwarfs the small decrease in hiring in Panel B. Here we see that many occupations do not register a statistically significant decrease in hiring in April 2020. However, a few do stand out: food preparation and serving occupations experienced a 6 percentage point decrease in hiring in April 2020, while cleaning and maintenance occupations saw a 3 percentage point decline. The occupations with larger decreases in hiring are clustered at the low end of the wage spectrum; however, two mid-ranked occupations (construction and community/social services) also experienced a 2-3 percentage point decrease in hiring rates.

Panel C of Figure 2 analyzes exit rates from each occupation. Here we see even more dramatic differences. For food preparation and serving occupations there is a 48 percentage point increase in the share of individuals employed in February 2020 who are now non-employed. Personal care occupations shed an extra 58 percentage points of their workers between February and April. Other occupations with exit rate increases of over 20 percentage points include cleaning and maintenance (rank 4), transportation (rank 6), production (rank 7), construction (rank 11), and arts and entertainment (rank 15). The highest wage-rank occupations, such as management, engineering, legal and computer occupations, all have exit rate increases of under 10 percentage points. Thus, the lowest-wage occupations are clearly the worst affected by the dramatic rise in job loss.

We next turn our attention to industries rather than occupations. Figure 3 shows how employment losses are distributed across industries, once again ranked from lowest-paying on the left to highest-paying on the right, as listed in Table 2. Panel A shows widespread impacts on employment, with the largest declines being in the Leisure and Hospitality sector (the lowest-paying industry), and the Education and Health Services sector (ranked 6th from the bottom). Declines are small in the Agricultural sector (second lowest-paying), as well as in some high-paying sectors such as Information, Public Administration and Mining.

In the remaining panels of Figure 3 we analyze the changes in industry-level inflows and outflows.[19] In Panel B we again see that most industries did not see a statistically

[18]The estimated coefficients from Panels B and C are detailed in Appendix Table A.1.

[19]The estimated coefficients from Panels B and C are detailed in Appendix Table A.2

significant decrease in hiring as of April 2020. However, three industries stand out: Leisure and Hospitality (4.9 percentage point decline), Information (3.3 percentage point decline), and Construction (2.5 percentage point decline). Meanwhile, Panel C shows that Leisure and Hospitality workers saw a 42 percentage point increase in exit rates in April 2020 and workers in Other Services industries saw a 35 percentage point increase. No other industries had an increase over 20 percentage points, while the four highest-paying industries (Public Administration, Professional Services, Financial Activities, and Mining) all saw increases in exit rates of under 12 percentage points.

The key takeaway from these results is that the pandemic has disproportionately affected low-wage jobs, with particularly dramatic effects on service-sector occupations and industries. In order to investigate whether both the occupation and the industry dimensions are independently informative, we focus on the two industries with the largest increase in exit rates: Leisure and Hospitality, and Other Services. We then replicate the exit specification from Figure 2 *within* these industries, focusing on the larger occupational groups that are employed therein.[20] Figure 4 shows that there is a strong relationship between occupational wage ranks and exit rates, even within these industries. The lowest-wage occupations (Food Preparation, Personal Care, and Cleaning) exhibit increases in exit rates of over 45 percentage points, while the high-pay managerial occupations show an increase in exit rates of 18 percentage points. For each occupational group, exit rates are higher within the service sector compared with the average for the occupation, indicating that displacement is worse across occupations in more-affected industries. This confirms that both the occupation and the industry dimensions are informative about job loss, in both cases indicating higher job destruction rates for lower-paid jobs.

3.2 Heterogeneous Impacts across Demographic Subgroups

It is well known that the demographic composition of employment varies substantially between high- and low-paying jobs, with women and non-white, less educated, and younger workers over-represented in low-wage jobs. We show this directly in Appendix Figures A.2 and A.3.

Table 3 presents the estimated impact of the pandemic on the employment outcomes of different demographic groups, once again using our regression approach to account for group-specific seasonality patterns and longer-term trends. Column (1)

[20]SOC 2-digit occupations with at least 150 observations in February 2020 in the matched data.

displays the employment-to-population ratio for each group in the pre-pandemic period of February 2020. Columns (2) and (3) show the estimated impact on this ratio, in percentage points, while Columns (4) and (5) show the estimated impact as a proportion of the group's total employment in February 2020. Several interesting results emerge. Both male and female employment to population ratios fall by approximately the same amount (12 percentage points). This, however, translates into significantly different declines in terms of the share of employment lost: 18% in the case of men and 22% in the case of women. This is due to the lower baseline employment rate for women. We can therefore infer that the pandemic had a stronger impact on women, given that a larger proportion of female employment was lost as compared to the fraction of lost male employment.

When considering differences across education groups, we see a monotonic pattern when focusing on the share of employment lost, as displayed in Column (4): the largest employment losses are among individuals with no high school degree, where the pandemic eliminated more than one-third of employment for this group between February and April 2020. Meanwhile, pandemic-related employment losses were below 9% for workers with a college degree. The remaining rows of Table 3 show larger employment losses for non-white workers, particularly Hispanics, as well as substantially larger losses for workers under 25 compared to older workers.

In Columns (6) through (10) we analyze the impact on labor market flows by demographic group. As before, flows are expressed relative to employment two months previously. We display the coefficient for April 2020, which reflects the change in flows from February to April relative to employment in February 2020, after controlling for typical transition rates for that demographic. Across demographics, we see that, consistent with the patterns observed for employment stocks, female workers, non-white workers (and particularly Hispanics), young workers, and those with less education experienced both larger increases in exit rates and larger decreases in hire rates. The comparison of Columns (4) and (10) indicates that the stock- and flow-based measures of employment contraction produce similar estimates for the percentage change in employment, confirming the reliability of an analysis based on flows, in spite of the recent increase in attrition rates.

Overall, we observe similar patterns in job loss across demographics as in past recessions, as documented by Hoynes et al. (2012), with the major exception being the rates for men. Recessions often are worse for men; however, we have found substantially larger impacts on women, consistent with what Alon et al. (2020) hypothesized.

Although the main driver in employment changes are exit rates, we do see that the decrease in youth hiring is four times that of older workers, a result that is consistent with Forsythe (2020), that shows firms disproportionately reduce hiring of young workers during recessions.

3.3 Do Occupations and Industries Explain Heterogeneous Impacts across Demographic Subgroups?

So far we have shown the dramatically differential impacts of the Covid-19 crisis across occupations and industries as well as across demographic groups. In this section, we investigate whether the disproportionate employment losses experienced by disadvantaged demographic groups are due to the fact that they are over-represented in the jobs that contracted most sharply (as shown in Figures A.2 and A.3), or if these workers experienced worse losses *within* job categories.

In order to answer this question, we focus on outflows from employment, which, as shown above, are the dominant margin of adjustment driving the employment decline during the crisis. The use of outflow data allows us to consider the pre-displacement occupation and industry for all workers switching out of employment, including those who transition out of the labor force.[21] We determine the extent to which the differential impact of the pandemic across demographic groups is accounted for by their pre-displacement occupation and industry by running a new set of regressions as follows:

$$\begin{aligned} Y_{it} = {} & \omega D_{demo(i)} + \theta D_{2020M3} + \delta D_{2020M4} \times D_{demo(i)} + \gamma D_{m(t)} \times D_{demo(i)} \\ & + \rho D_{occ(it)} + \beta D_{2020M4} \times D_{occ(it)} + \alpha D_{y(t)} + \epsilon_{it} \end{aligned} \tag{2}$$

Equation (2) differs from Equation (1) in two ways. First, instead of running regressions using observations at the demographic group level, we now directly use the individual-level data, pooling all demographic groups together. Y_{it} is an indicator variable which is equal to one for individuals who transition out of employment. We regress this on the interaction of demographic indicators with a dummy variable for April 2020,

[21] As we have seen, a substantial fraction of those exiting employment between February and April transitioned to being out of the labor force, and the CPS would not record the prior occupation or industry for the majority of these individuals in the cross-sectional data. An additional advantage of using the flow data is the fact that the occupational information for non-employed individuals is independently coded in the CPS. Independent coding is known to lead to substantial mismeasurement, even at highly aggregated levels of occupational classification (Kambourov & Manovskii, 2013; Moscarini & Thomsson, 2007).

while also controlling for year and demographic group fixed effects, as well as fully interacted calendar month and demographic group indicators. Our coefficient of interest, δ, estimates differential changes in exit rates across demographic groups, while still allowing for baseline and seasonal differences in each group's employment exit patterns. Second, we introduce successive occupation and industry fixed effects, both directly and interacted with the April 2020 indicator. This controls for differences in exit rates between job types under typical conditions, as well as differences in job loss by job type that are specific to the Covid-19 pandemic. To the extent that the differences between demographic groups are explained by their pre-displacement occupation or industry affiliation, the estimated coefficient $\widehat{\delta}$ should be driven to zero once these controls are introduced. An estimate of $\widehat{\delta}$ that differs from zero even after controlling for occupations or industries would indicate differential exit rates across demographic groups occurring *within* job types.

Figure 5 plots the estimated $\widehat{\delta}$ coefficients from Equation (2), along with 95% confidence intervals. We first show the baseline differentials between groups, before introducing any occupation or industry controls (blue bars). We then show results when introducing 2-digit occupation fixed effects (red bars), major industry groups (green bars), and both 2-digit occupation and major industry controls (orange bars). Finally, we show results from a specification that includes fixed effects at the most detailed occupation and industry levels available in the CPS (grey bars). All coefficients reported are relative to the omitted group, which in the respective panels are males, whites, 26-35 year olds, and college graduates. The estimated coefficients are also reported in Appendix Table A.3.

The top left panel shows that female employment exit rates increased by 3.5 percentage points more than male employment exit rates in April 2020. When we control for 2-digit occupations and major industry there is little difference in the gap, but once we control for detailed occupation and industry the gap disappears. This means that all of the elevated exit rate for women is due to the types of jobs they work in (at a detailed level), rather than differences within narrowly defined jobs.

The top right panel of Figure 5 shows that two-digit occupations can explain most of the increased exit rate for black workers over white workers. For Hispanics, the most detailed controls can explain at most 70% of the gap, meaning that 30% of the elevated exit rate for Hispanics is occurring within narrowly defined occupations and industries. For all other non-white races, the most detailed controls can account for only half of the gap.

In the bottom left panel of Figure 5 we see that workers under 25 had a 11.8 percentage point larger increase in exit rates compared to 26-35 year-olds. This difference is reduced by 66% after controlling for detailed occupations and industries. For the 56 and up age category, exit rates increased by 2 percentage points more than for 26-35 year-olds; this difference, however, does not change with the inclusion of occupation or industry controls – in fact, the differential becomes slightly larger when these controls are included – indicating that all of the increase in exit rates for older workers occurred within narrowly defined jobs.

In the bottom right panel of Figure 5 we see that individuals without a high school degree saw a pandemic-related increase in exit rates 18 percentage points larger than that of college graduates. Occupation and industry fixed effects bring the gap down to 6 percentage points, leaving 38% of the difference in exit rates unexplained. We see similar results for high school graduates and workers with some college, with the most detailed controls leaving 33% and 26% of the gaps unexplained, respectively.

The results from this analysis are summarized in Table 4. While differences in employment patterns across occupations and industries can account for a majority of the differences in the increase in exit rates across demographic groups for all groups except the oldest workers, only for women can all of the gap be explained by occupation and industry sorting. For most of the analyzed disadvantaged groups, at least 25% of the increase in job loss occurs *within* detailed occupations and industries. Hence, these workers are not only being affected by the fact that they tend to be segregated into more exposed occupations and industries, but they are also more likely to transition out of employment when compared to other workers in very similar jobs.

As a final way to visualize this pattern, Figure 6 illustrates the change between February and April 2020 in the *within-occupation* employment share of different groups. If the impacts across demographic groups were purely driven by occupation-level shocks, we would not expect to observe changes in these groups' shares of employment within occupations. The figure, however, shows that the shares of female, young, less-educated and non-white workers declined between February and April within the vast majority of 2-digit occupations. This confirms that these workers are experiencing disproportionate job displacement even within 2-digit occupations. Similar patterns are observed across industries in Appendix Figure A.4.

4 Conclusion

The economic fallout from the Covid-19 pandemic has been widespread. The magnitude of the employment losses, however, has differed substantially across different types of jobs and different types of workers. This paper shows that the pandemic has had the effect of exacerbating pre-existing inequalities. Workers employed in lower-paying occupations and industries have been disproportionately impacted, given that employment declines have been significantly larger among lower-paying job categories. These asymmetric occupation- and industry-level effects may reflect heterogeneities in the extent to which different jobs can be performed remotely (see Brynjolfsson et al., 2020; Dingel & Neiman, 2020), as well as differences in which types of businesses have been allowed to continue to operate during the pandemic.

Importantly, the differential impact on disadvantaged groups extends beyond their exposure due to their occupation and industry affiliation. Even within detailed occupations and industries we find that Hispanic, less-educated, and younger workers have suffered disproportionate declines in their employment rates.

Going forward, it will be important for policymakers to pay particular attention to these disadvantaged groups, who were not only more likely to be in a constrained economic situation before the pandemic, but have also been disproportionately likely to be impacted by it.

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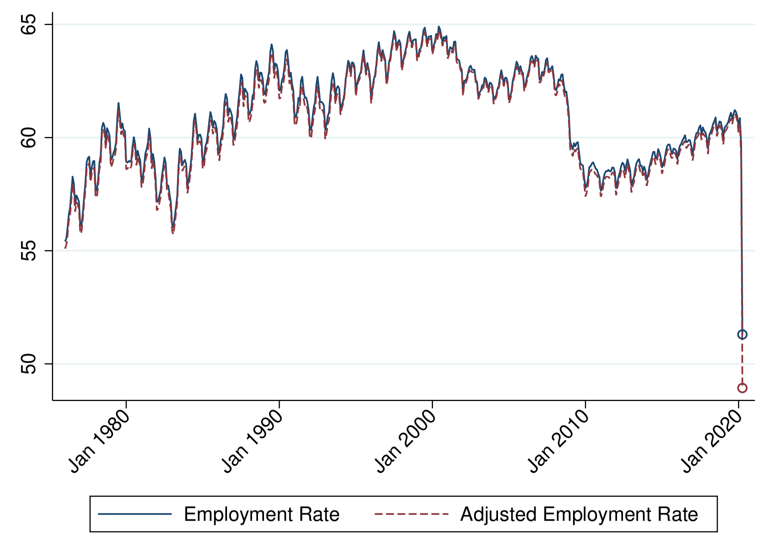
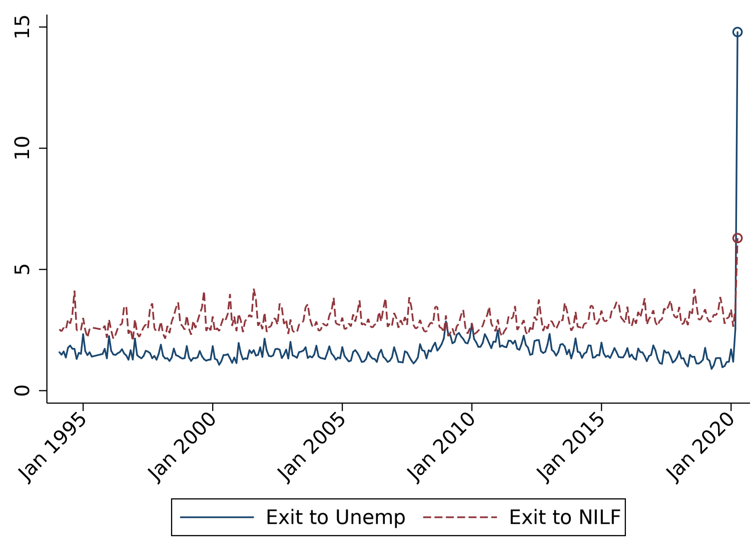
Figure 1: Aggregate Employment Rate and Labor Market Flows

Panel A: Employment Rate (%)



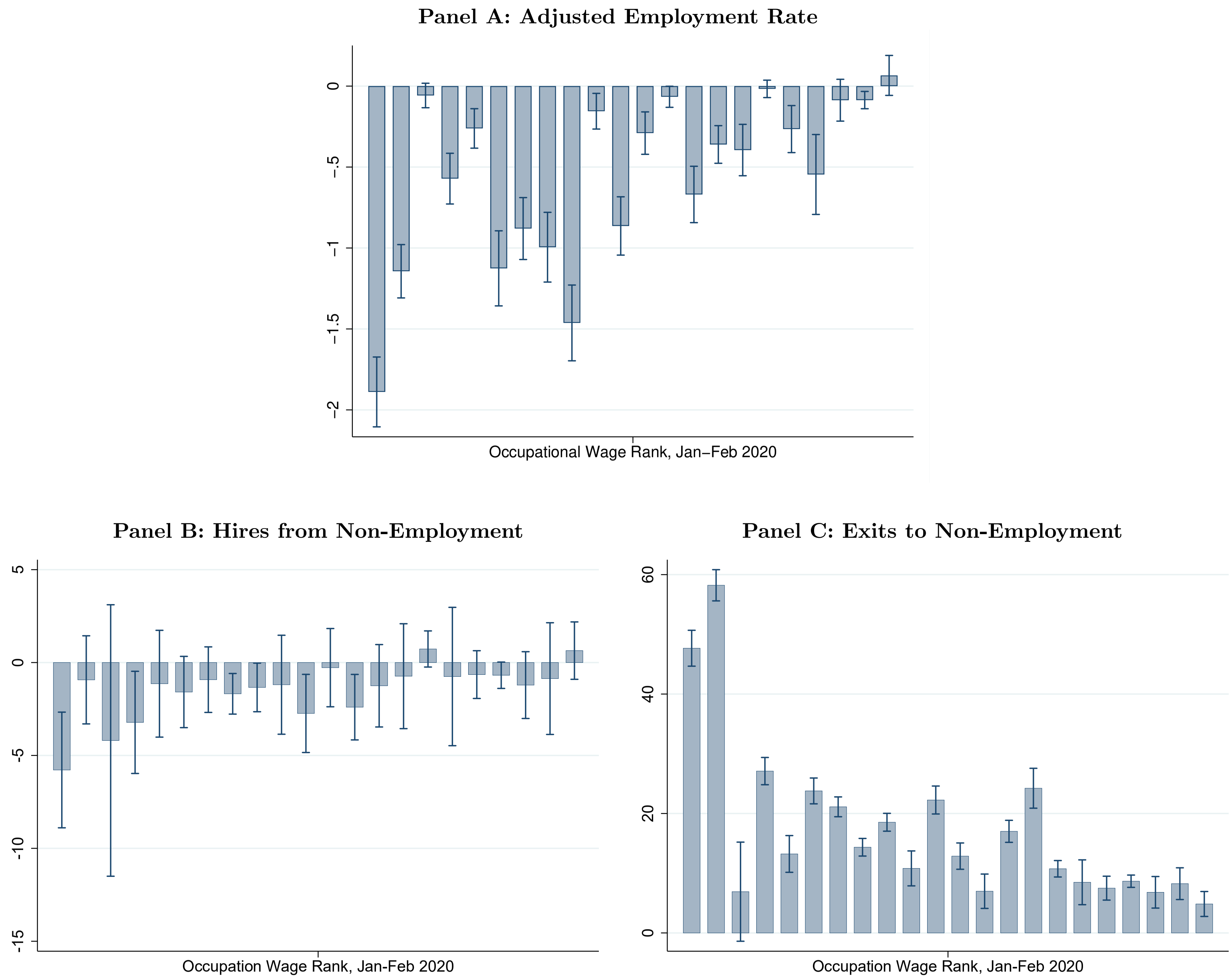
Panel B: Outflows from Employment (%)



Panel C: Inflows to Employment (%)

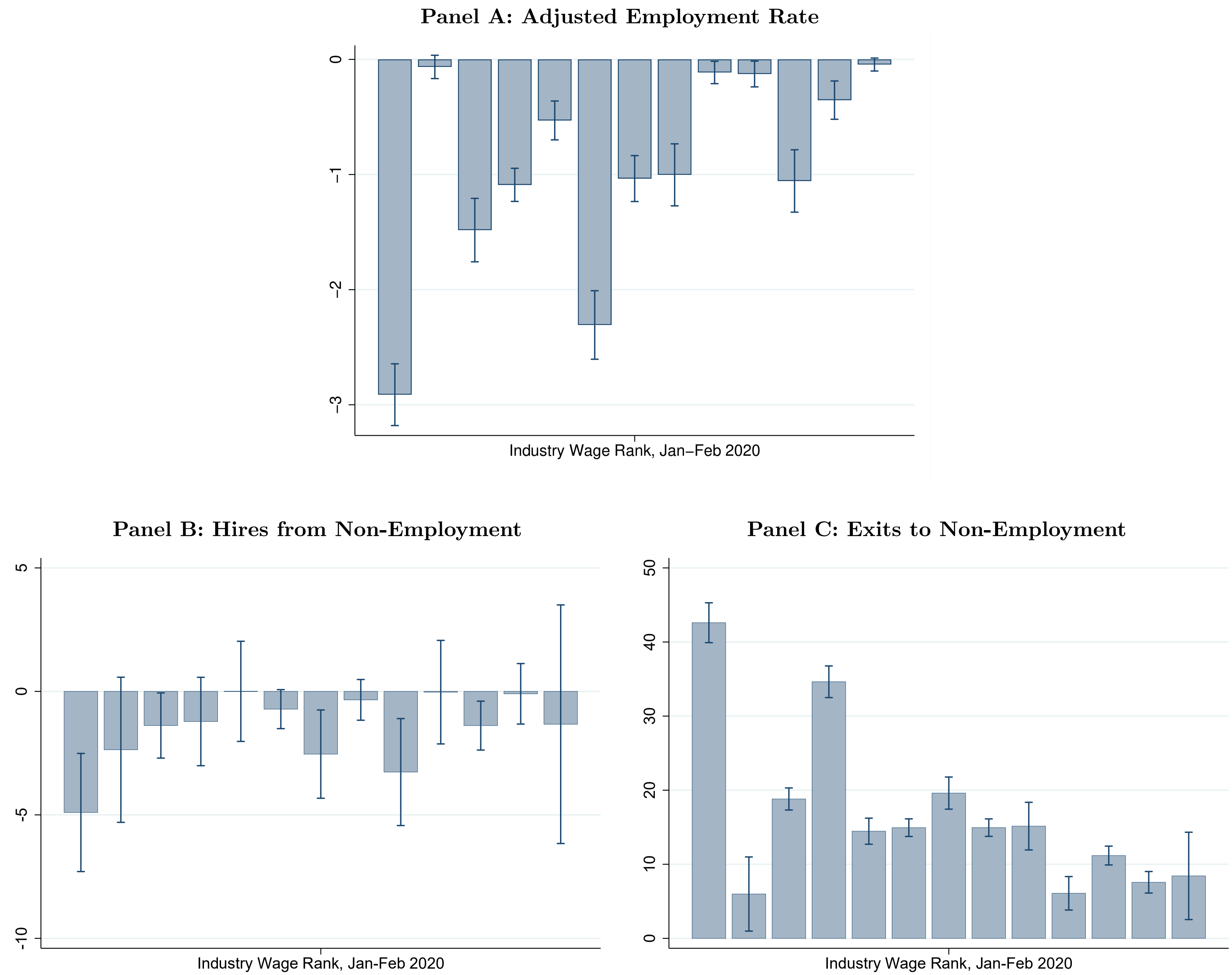
Note: The figure plots monthly employment rates and labor market flows (percent of employed individuals who exit employment to non-employment each month, and percent of non-employed individuals who become employed each month as a share of the previous month's employment) based on monthly CPS data. The adjusted employment rate excludes individuals who are classified as employed, but were absent from work during the reference week for "other" reasons and report not being paid by their employer for their time off. These workers are instead classified as unemployed. The flow variables use the adjusted employment and unemployment classifications.

Figure 2: Impact of the Pandemic across Occupations, April 2020



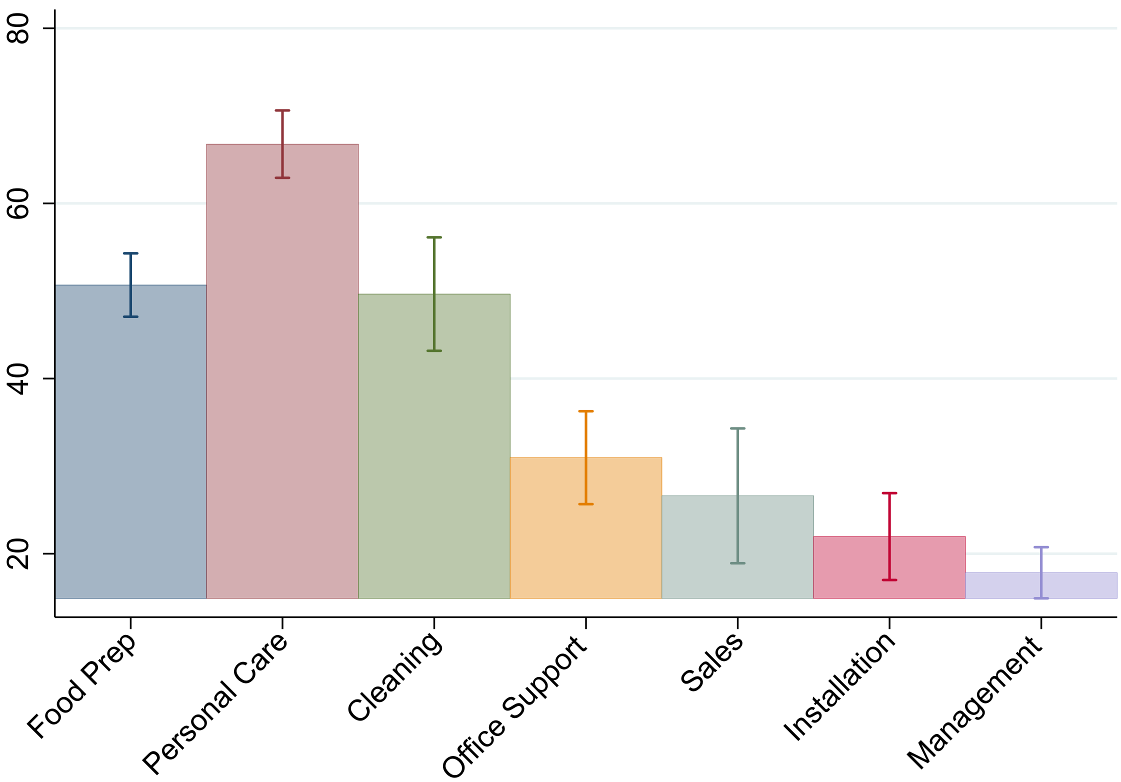
Note: The figure plots the estimated coefficient $\widehat{\delta}_g$ from Equation (1) for each 2-digit occupation, indicating the change in the dependent variable in April 2020 after controlling for seasonality and year fixed effects. Occupations are ranked from lowest- to highest-paying based on their mean wage in January and February 2020. Full details of the ranking and employment changes for each 2-digit occupation are provided in Table 1. The estimated coefficients from Panels B and C are listed in Appendix Table A.1.

Figure 3: Impact of the Pandemic across Industries, April 2020



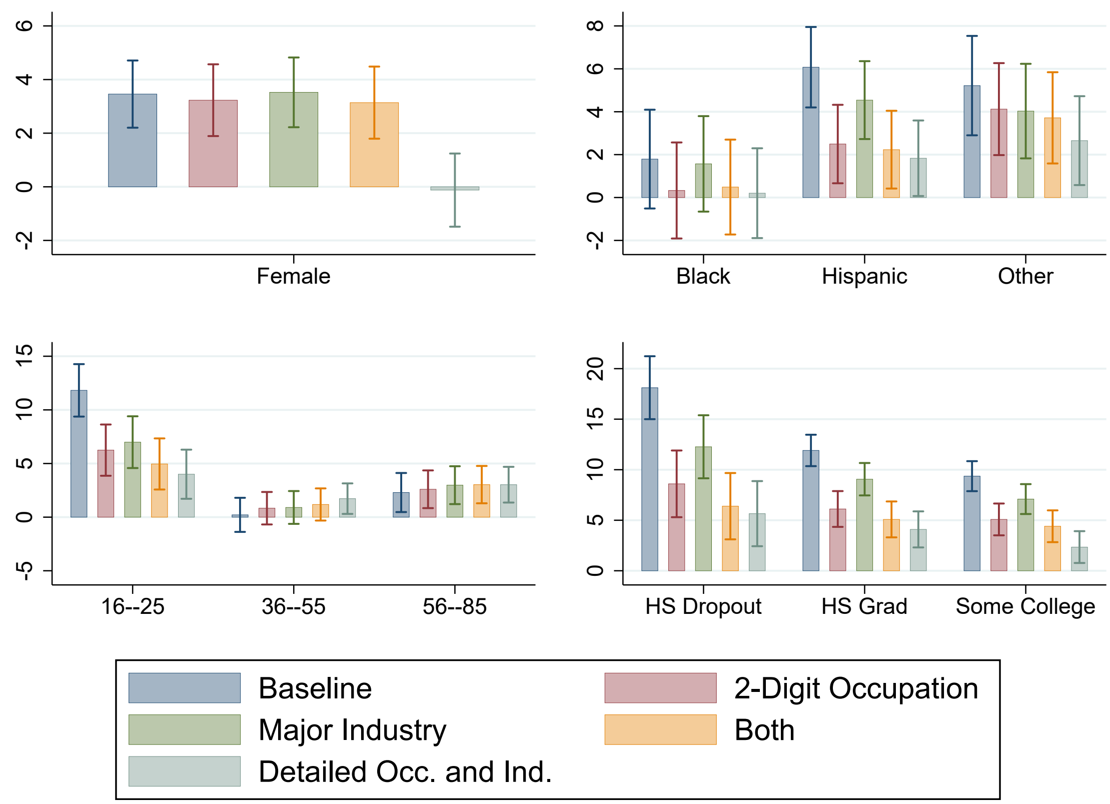
Note: The figure plots the estimated coefficient $\widehat{\delta}_g$ from Equation (1) for each major industry category, indicating the change in the dependent variable in April 2020 after controlling for seasonality and year fixed effects. Industries are ranked from lowest- to highest-paying based on their mean wage in January and February 2020. Full details of the ranking and employment changes for each industry are provided in Table 2. The estimated coefficients from Panels B and C are listed in Appendix Table A.2.

Figure 4: Impact of the Pandemic on Employment Exit Rates across Occupations within Service Industries, April 2020



Note: The figure plots the estimated coefficient $\widehat{\delta}_g$ from Equation (1) for each occupation, using data from the Leisure and Hospitality, and Other Service industries only. The estimated coefficients indicate the change in the exit rate for each occupation in April 2020 after controlling for seasonality and year fixed effects. Occupations are ranked from lowest- to highest-paying based on their mean wage in January and February 2020.

Figure 5: Exits from Employment: Differentials across Demographic Groups with Different Sets of Fixed Effects



Note: The figure displays the estimated coefficients $\widehat{\delta}$ from Equation (2) across demographic groups, indicating the change in the probability of transitioning out of employment for each demographic group between February and April 2020, relative to the omitted category (males, whites, 26-35 year olds, and college graduates, respectively), after controlling for group-specific seasonality as well as year fixed effects. Each bar color represents the results from a regression that includes a different set of occupation or industry controls (directly and interacted with an April 2020 dummy), as listed at the bottom of the graph.

Figure 6: Changes in demographic shares within 2-digit occupations, February–April 2020

Note: The figure plots the change in the share of different demographic groups among workers in each 2-digit occupation over the course of the pandemic (February to April 2020). Occupations are ranked based on their average wages in the pre-pandemic period of January and February 2020. The size of each circle is proportional to the size of the occupation in February 2020.

Table 1: Changes in Employment by Occupation

2-digit SOC	Occupation	Wage Rank (1=lowest)	Log Real Wage (Jan-Feb 2020)	Δ Emp/Pop Feb-Apr 2020
35	Food Prep and Serving	1	2.22	-1.81
39	Personal Care, Service	2	2.42	-1.03
45	Farm, Fish, Forestry	3	2.45	-0.04
37	Cleaning, Maintenance	4	2.46	-0.51
31	Healthcare Support	5	2.50	-0.29
53	Transportation	6	2.63	-1.01
51	Production	7	2.69	-0.84
43	Office/Admin Support	8	2.69	-1.03
41	Sales and Related	9	2.73	-1.41
33	Protective Service	10	2.85	-0.17
47	Construction, Extraction	11	2.88	-0.81
49	Installation, Maintenance	12	2.89	-0.32
21	Community/Social Service	13	2.96	-0.06
25	Education	14	2.98	-0.62
27	Arts, Entertainment, Media	15	3.06	-0.34
29	Healthcare	16	3.22	-0.43
19	Science	17	3.26	-0.02
13	Business/Financial Op	18	3.28	-0.28
11	Management	19	3.33	-0.53
17	Architecture/Engineering	20	3.41	-0.11
23	Legal	21	3.43	-0.07
15	Computer/Mathematical	22	3.43	0.02

Note: Occupations are ranked from lowest- to highest-paying based on their mean wage in January and February 2020. Our employment measure excludes individuals who were absent from work during the reference week for "other" reasons and report not being paid by their employer for their time off.

Table 2: Changes in Employment by Industry

BLS Code	Industry	Wage Rank (1=lowest)	Log Real Wage (Jan-Feb 2020)	Δ Emp/Pop Feb-Apr 2020
11	Leisure & Hospitality	1	2.41	-2.73
1	Agriculture	2	2.52	-0.04
5	Trade	3	2.67	-1.58
12	Other Services	4	2.72	-1.07
6	Transp & Utilities	5	2.92	-0.49
10	Educational & Health	6	2.93	-2.27
3	Construction	7	2.94	-0.96
4	Manufacturing	8	2.96	-0.95
7	Information	9	3.08	-0.15
13	Public Administration	10	3.08	-0.15
9	Professional & Business	11	3.11	-0.93
8	Financial Activities	12	3.16	-0.36
2	Mining	13	3.28	-0.05

Note: Industries are ranked from lowest- to highest-paying based on their mean wage in January and February 2020. Our employment measure excludes individuals who were absent from work during the reference week for "other" reasons and report not being paid by their employer for their time off.

Table 3: Impact of the Pandemic on Employment Stocks and Flows by Demographic Groups

	Stocks					Flows				
	Feb 2020	Emp Rate Chg (p.p.)		Emp Chg (%)		Exits		Hires		(Hires-Exits)
	Emp Rate	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE	(%)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Male	65.91	-12.15***	(0.17)	-17.81***	(0.40)	16.09***	(0.32)	-1.08***	(0.25)	-17.17
Female	55.73	-12.10***	(0.24)	-21.78***	(0.55)	19.33***	(0.37)	-1.57***	(0.28)	-20.90
No HS Deg.	34.41	-11.80***	(0.70)	-34.83***	(2.99)	28.56***	(1.50)	-4.71***	(1.28)	-33.27
HS Grad.	56.00	-14.64***	(0.36)	-28.41***	(1.30)	22.87***	(0.48)	-1.63***	(0.39)	-24.50
Some Col.	61.71	-14.37***	(0.35)	-22.81***	(1.18)	20.09***	(0.44)	-1.28**	(0.39)	-21.37
Col. Grad.	72.57	-8.96***	(0.29)	-8.99***	(0.87)	10.97***	(0.32)	-0.51*	(0.24)	-11.48
White	59.94	-10.62***	(0.15)	-17.51***	(0.35)	15.83***	(0.28)	-1.12***	(0.20)	-16.95
Black	58.18	-12.55***	(0.45)	-21.38***	(1.12)	17.62***	(0.87)	-1.37	(0.72)	-18.99
Hispanic	64.50	-16.57***	(0.54)	-25.52***	(1.13)	22.21***	(0.67)	-2.10**	(0.60)	-24.31
Other	61.71	-13.69***	(0.43)	-20.98***	(1.25)	21.22***	(0.80)	-1.08	(0.87)	-22.3
16 to 25	53.62	-18.16***	(0.56)	-35.15***	(1.62)	26.82***	(1.14)	-4.17***	(1.11)	-30.99
26 to 35	80.66	-14.74***	(0.37)	-17.26***	(0.79)	15.68***	(0.39)	-0.68	(0.35)	-16.36
36 to 55	79.56	-12.66***	(0.27)	-15.76***	(0.47)	15.32***	(0.26)	-0.94***	(0.26)	-16.26
56 to 85	37.49	-7.47***	(0.25)	-19.49***	(0.93)	18.02***	(0.56)	-0.96**	(0.35)	-18.98

Note: The table lists the estimated coefficients $\widehat{\delta}_g$ from Equation (1) for each demographic group, indicating the change in the dependent variable (employment, exits or hires) in April 2020 after controlling for seasonality and year fixed effects.

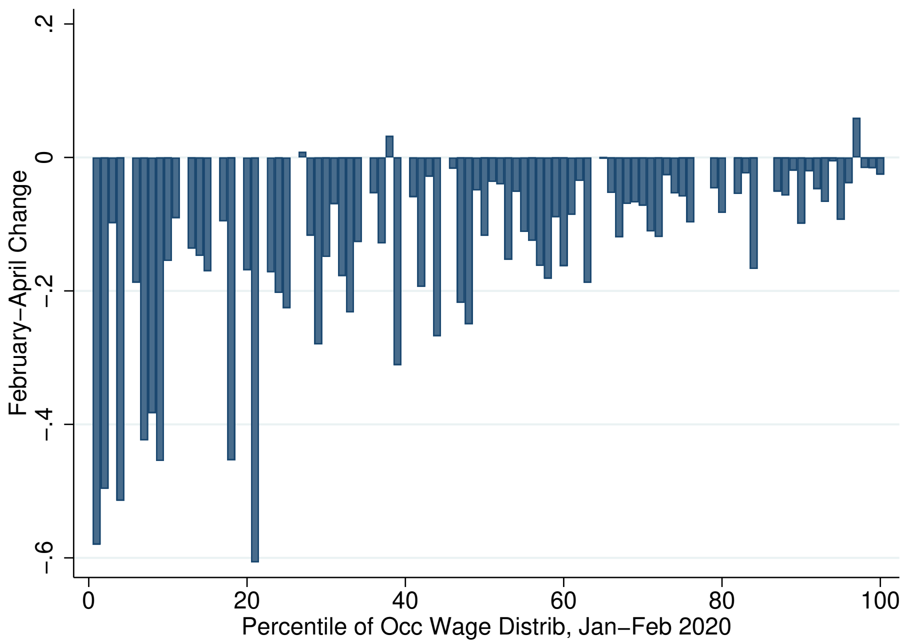
Table 4: Share of Increased Exit Rates Explained by Occupation and Industry

		Share explained by:					
	Gap	2-Dig SOC Occ.	Major Ind.	Both	Detailed Occ.	Detailed Ind.	Both Detailed
Female	3.46	6.6	-1.7	9.2	79.8	72.8	102.9
16 to 25	11.8	47.0	40.8	58.0	57.6	44.2	66.1
35 to 55	0.21	495.2	-328.6	-461.9	-414.3	-533.3	-719
56 to 85	2.30	-13.0	-29.6	-31.7	-15.2	-24.8	-31.7
No HS Degree	18.1	52.5	32.6	64.7	61.9	32.6	68.8
HS Graduate	11.9	49.9	24.5	58.8	62.5	30.1	67.3
Some College	9.36	44.7	23.2	51.8	68.1	35.9	73.8
Black	1.79	81.6	12.3	72.6	111.2	11.2	88.8
Hispanic	6.08	59.0	25.3	63.3	71.1	38.2	69.9
Other Non-White	5.22	21.1	22.8	28.9	48.9	33.9	49.2

Note: The first column displays the estimated gap in the impact of the pandemic on employment exit rates for each demographic group relative to the omitted category (males, whites, 26-35 year olds, and college graduates, respectively) based on the regression results in Table A.3. The remaining columns display the fraction of this gap that can be accounted for by workers' pre-displacement occupation and industry.

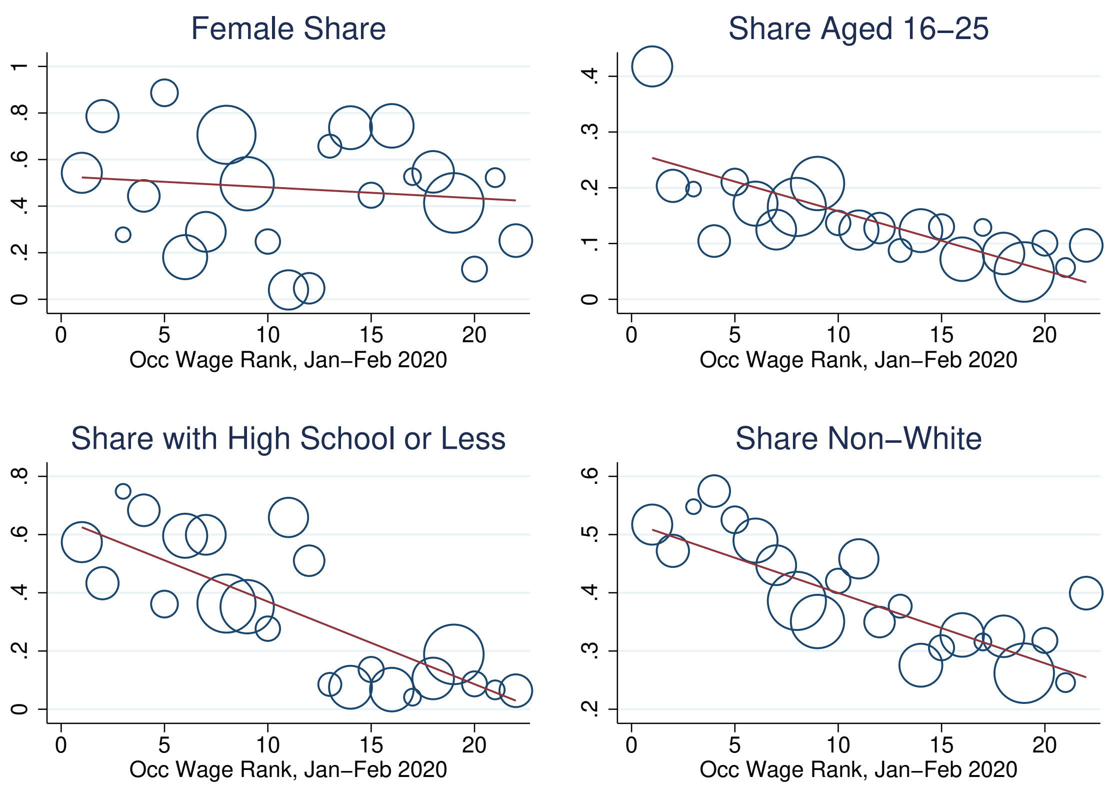
A Appendix

Figure A.1: Changes in Employment across 4-Digit Occupations, February–April 2020



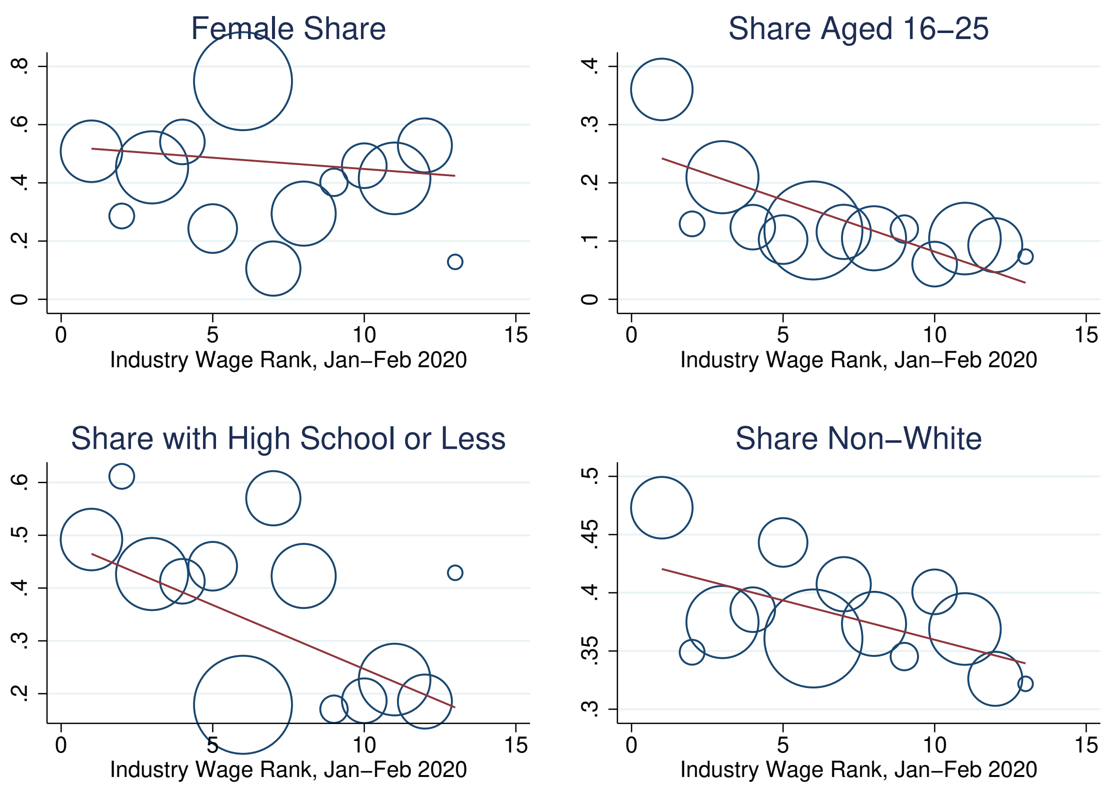
Note: The figure plots changes between February and April 2020 in adjusted employment rates for occupations at each percentile of the employment-weighted occupational wage distribution (where the assignment to percentiles is based on employment and wages in the pre-pandemic period of January and February 2020).

Figure A.2: Demographic Shares within 2-digit Occupations, February 2020



Note: The figure plots the share of different demographic groups among workers in each 2-digit occupation before the onset of the pandemic (February 2020). Occupations are ranked based on their average wages in the pre-pandemic period of January and February 2020. The size of each circle is proportional to the size of the occupation in February 2020.

Figure A.3: Demographic Shares within Major Industries, February 2020



Note: The figure plots the share of different demographic groups among workers in each major industry category before the onset of the pandemic (February 2020). Industries are ranked based on their average wages in the pre-pandemic period of January and February 2020. The size of each circle is proportional to the size of the industry in February 2020.

Figure A.4: Changes in Demographic Shares within Major Industries, February–April 2020

Note: The figure plots the change in the share of different demographic groups among workers in each major industry over the course of the pandemic (February to April 2020). Industries are ranked based on their average wages in the pre-pandemic period of January and February 2020. The size of each circle is proportional to the size of the industry in February 2020.

Table A.1: Estimated Coefficients from Figure 2

	Exits (Panel C)		Hires (Panel B)	
	Coef.	SE	Coef.	SE
Food Prep and Serving	47.67***	(1.49)	-5.78***	(1.54)
Personal Care	58.22***	(1.30)	-0.93	(1.18)
Farm, Fish, Forestry	6.90	(4.11)	-4.19	(3.62)
Cleaning, Maintenance	27.10***	(1.13)	-3.22*	(1.36)
Healthcare Support	13.23***	(1.53)	-1.14	(1.43)
Transportation	23.78***	(1.07)	-1.59	(0.95)
Production	21.12***	(0.82)	-0.92	(0.87)
Office/Admin Support	14.35***	(0.73)	-1.68**	(0.54)
Sales and Related	18.53***	(0.74)	-1.34*	(0.65)
Protective Service	10.80***	(1.45)	-1.19	(1.32)
Construction, Extraction	22.26***	(1.16)	-2.74*	(1.04)
Installation, Maintenance	12.86***	(1.09)	-0.27	(1.04)
Community/Social Service	6.98***	(1.43)	-2.40**	(0.87)
Education	17.01***	(0.91)	-1.25	(1.10)
Arts, Entertainment, Media	24.23***	(1.66)	-0.73	(1.40)
Healthcare	10.74***	(0.68)	0.73	(0.48)
Science	8.48***	(1.86)	-0.75	(1.85)
Business/Financial Op	7.50***	(0.99)	-0.65	(0.64)
Management	8.66***	(0.51)	-0.68+	(0.35)
Engineering	6.80***	(1.31)	-1.21	(0.89)
Legal	8.25***	(1.32)	-0.86	(1.49)
Computer/Mathematical	4.84***	(1.04)	0.64	(0.77)

The table lists the estimated coefficients $\widehat{\delta}_g$ from Equation (1) for each 2-digit occupation, indicating the change in the dependent variable (exits or hires) in April 2020 as a fraction of employment in February 2020 after controlling for seasonality and year fixed effects. Occupations are ranked from lowest- to highest-paying based on their mean wage in January and February 2020.

Table A.2: Estimated Coefficients from Figure 3

	Exits (Panel C)		Hires (Panel B)	
	Coef.	SE	Coef.	SE
Leisure and Hospitality	42.60***	(1.33)	-4.90***	(1.19)
Agriculture, Forestry, Fishing	5.98*	(2.48)	-2.36	(1.46)
Wholesale and Retail Trade	18.81***	(0.74)	-1.38*	(0.65)
Other Services	34.63***	(1.06)	-1.22	(0.89)
Transportation and Utilities	14.46***	(0.87)	0.00	(1.01)
Educational and Health Services	14.94***	(0.59)	-0.72+	(0.39)
Construction	19.61***	(1.08)	-2.54**	(0.89)
Manufacturing	14.95***	(0.58)	-0.34	(0.41)
Information	15.15***	(1.59)	-3.27**	(1.07)
Public Administration	6.08***	(1.12)	-0.03	(1.04)
Professional and Business Services	11.18***	(0.63)	-1.39**	(0.49)
Financial Activities	7.57***	(0.72)	-0.10	(0.61)
Mining	8.43**	(2.92)	-1.33	(2.40)

Note: The table lists the estimated coefficients $\widehat{\delta}_g$ from Equation (1) for each major industry, indicating the change in the dependent variable (exits or hires) in April 2020 as a fraction of employment in February 2020 after controlling for seasonality and year fixed effects. Industries are ranked from lowest- to highest-paying based on their mean wage in January and February 2020.

Table A.3: Estimated Demographic Group Differentials in Transition Rates out of Employment with Different Sets of Fixed Effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Panel A: Gender						
April 2020 × Female	3.46***	3.23***	3.52***	3.14***	0.70	0.94	-0.12
	(0.64)	(0.68)	(0.66)	(0.69)	(0.71)	(0.66)	(0.70)
	Panel B: Age						
April 2020 × 16 to 25	11.82***	6.25***	6.99***	4.96***	5.00***	6.59***	4.00***
	(1.25)	(1.22)	(1.23)	(1.22)	(1.20)	(1.19)	(1.17)
April 2020 × 36 to 55	0.21	0.83	0.90	1.18	1.08	1.33+	1.72*
	(0.81)	(0.77)	(0.78)	(0.76)	(0.75)	(0.74)	(0.73)
April 2020 × 56 to 85	2.30*	2.60**	2.98***	3.03***	2.65**	2.87***	3.03***
	(0.93)	(0.90)	(0.90)	(0.89)	(0.87)	(0.87)	(0.85)
	Panel C: Education						
April 2020 × No HS Degree	18.11***	8.60***	12.27***	6.39***	6.90***	12.21***	5.65***
	(1.59)	(1.68)	(1.59)	(1.67)	(1.69)	(1.56)	(1.64)
April 2020 × HS Degree	11.91***	6.11***	9.06***	5.08***	4.65***	8.41***	4.09***
	(0.79)	(0.90)	(0.82)	(0.91)	(0.92)	(0.83)	(0.91)
April 2020 × Some College	9.36***	5.08***	7.09***	4.41***	2.89***	5.90***	2.35**
	(0.76)	(0.80)	(0.75)	(0.80)	(0.81)	(0.76)	(0.80)
	Panel D: Race and Ethnicity						
April 2020 × Black	1.79	0.33	1.57	0.49	-0.24	1.59	0.20
	(1.17)	(1.14)	(1.14)	(1.13)	(1.10)	(1.10)	(1.07)
April 2020 × Hispanic	6.08***	2.49**	4.54***	2.23*	1.76+	3.76***	1.83*
	(0.96)	(0.93)	(0.93)	(0.92)	(0.92)	(0.90)	(0.90)
April 2020 × Other	5.22***	4.12***	4.03***	3.71***	2.67*	3.45**	2.65*
	(1.18)	(1.09)	(1.12)	(1.09)	(1.08)	(1.07)	(1.06)
Observations	1,636,655	1,636,655	1,636,655	1,636,655	1,636,638	1,636,651	1,636,634
Fixed Effects	None	2 Dig. SOC	Maj. Ind.	Both	Detailed Occ	Detailed Ind.	Both Detailed

Note: The table displays the estimated coefficients $\widehat{\delta}$ from Equation (2) across demographic groups. The dependent variable is an indicator variable equal to one for individuals who transition out of employment over a 2-month window (e.g. February–April). Each column includes a different set of fixed effects (directly and interacted with an April 2020 dummy), as listed in the bottom row of the table. Each panel represents a separate regression along a different demographic dimension.